Impact of traffic on air pollution in a mid-sized urban city during COVID-19 lockdowns

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Abstract

In this study, we evaluated the changes in air pollutant concentrations around Milwaukee, WI, during and after lockdown due to the COVID-19 pandemic for a period of 126 days. Measurements of particulate matter (PM_1, $PM_{2.5}$, and PM_{10}), NH_3, H_2S, and $O_3 + NO_2$, were made on a 74-km route of arterial and highway roads from April to August 2020 using a Sniffer 4D sensor mounted to a vehicle. Traffic volume during measurement periods were estimated from smartphone-based traffic data. From lockdown (March 24, 2020–June 11, 2020) to post-lockdown (June 12, 2020–August 26, 2020) median traffic volume increased roughly 30–84%, depending upon the road type. In addition, increases in mean concentrations of NH_3 (277%), PM (220–307%), and $O_3 + NO_2$ (28%) were also observed. For both traffic and air pollutants, abrupt changes in the data were observed mid-June, shortly after lockdown measures were lifted in Milwaukee County. Indeed, traffic was able to explain up to 57% of PM, 47% of NH_3, and 42% of $O_3 + NO_2$ variance in pollutant concentrations on arterial and highway road segments. Two arterial roads that did not have statistically significant changes in traffic patterns during the lockdown exhibited no statistically significant trends between traffic and air quality parameters. This study demonstrated that COVID-19 lockdowns in Milwaukee, WI, caused significant decreases in traffic, which in turn had a direct impact on air pollutants. It also highlights the need for traffic volume and air quality data at relevant spatial and temporal scales for accurately assessing source apportionment of combustion-based air pollutants, which cannot be captured with typical ground-based sensor systems.

Keywords COVID-19 · Air pollutants · Traffic · Emissions

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Introduction

Air pollution is a significant threat to human health and a rising cause of illness and mortality around the world (Manisalidis et al. 2020). In the USA, air pollution is responsible for between 5 and 10 percent of all premature deaths (Joint and Organization 2006; Landrigan et al. 2018). Many of the air pollutants that negatively impact human health are driven by combustion emissions from various sources including traffic and power generation. These pollutants include particulate matter (PM) and ammonia (NH_3), which can cause respiratory diseases, nervous system dysfunctions, and cancers (Brugha and Grigg 2014; Chen et al. 2016; Wu et al. 2018). Other combustion pollutants in high levels, such as nitrogen dioxide (NO_2) and ozone (O_3), can negatively affect respiratory and cardiovascular systems (Guo et al. 2021; Huangfu and Atkinson 2020; Valavanidis et al. 2013).

Traffic is a significant portion of these combustion pollutants in many urban areas and has been shown to contribute up to 34% of particulate matter (Ouyang et al. 2015a, b; Thurston et al. 2011), 61% of NH_3 (Durbin et al. 2002; Elser et al. 2018; Pan et al. 2020), 25% of O_3 (Li et al. 2016; Pay et al. 2019; Valverde et al. 2016), and 50% of NO_2 emissions (Environmental Protection Agency (EPA), 1999; Nguyen et al. 2018). However, despite evidence of the contribution of traffic combustion to air pollutants, it is unclear if and to what extent traffic management strategies could improve urban air quality due to a lack of post-evaluation of implemented strategies (York Bigazzi and Rouleau 2017). This unclarity in how traffic management strategies could improve air quality stems, in part, from a lack of spatial and temporal experimental data on the impacts of traffic reductions on air quality.

The lockdowns during the COVID-19 pandemic presented an opportunity to help fill this gap through an unprecedented change in traffic patterns. Across the world, there were significant decreases in traffic due to the COVID-19 lockdowns. For example, in South Korea, traffic decreased 9.7% (Du et al. 2021), and in the USA, traffic was reduced to 40–65% (Hudda et al. 2020; Xiang et al. 2020). Air quality also changed during this period, with observed decreases in air pollutants in many cities and countries across the world (Adam et al. 2021; Chauhan and Singh 2020; Gkatzelis et al. 2021), such as an observed 25% reduction in $PM_{2.5}$ in cities in northern China (Bao and Zhang 2020) and a 32% decrease in NO_2 in England (Ropkins and Tate 2021).

Not surprisingly, studies have emerged that evaluate the relationship between traffic volume and air pollution during the COVID-19 lockdowns. However, the connection between traffic reductions and air quality during COVID lockdowns was not always clear or uniform across the world. There was a 53–60% decrease in air pollutants from traffic sources (NO_2, CO) during the lockdowns in Nanjing, China (Wang et al. 2020a, b), and in Somerville, MA, USA, there was a decrease in ultrafine particle number concentrations (45–69%) and black carbon (22–46%) that were attributed to traffic (Hudda et al. 2020). In addition, traffic reductions (48–60%) in six cities in Italy were observed alongside reductions in NO_2 (25–59%) and PM (17–32%) (Gualtieri et al. 2020), and in California, traffic reductions (24–29%) were observed alongside decreases in NO (32–35%) and NO_2 (15–29%) (Liu et al. 2020). Across northern China, air quality sensors in 366 urban centers were evaluated against traffic data, and it was found that traffic volume correlated between 11 and 44% to air pollutant concentrations ($PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and O_3) (Wang et al. 2020a, b). Others found less significant decreases in air pollutants due to traffic. Traffic-related emissions caused a decrease in pollutants (PM, NO, NO_2, and NOx) between 3 and 12% in Seattle, WA (Xiang 2020), and there was no observable decrease

in $PM_{2.5}$ and NO_2 in Memphis, TN, USA, even though traffic decreased 57% (Jia et al. 2020). The variations in findings could be due to differences in methods used to measure pollutants (e.g., remote sensing, fixed stations, or vehicle-mounted sensors), the specific pollutants measured, and unique meteorological or physiographic conditions of each city. In addition, these previous studies were either temporally constrained to traffic data at an average daily or hourly interval, spatially constrained to traffic and air pollutant data at single point sources, or both. This in turn limits the ability to derive relationships between traffic and air pollutants at the spatial scale of a single road segment, where traffic volumes and air pollutant concentrations can vary significantly. Therefore, additional studies that shed light on the changes in air quality due to the COVID-19 lockdown using data in high spatial and temporal resolutions are essential to improve our understanding of the impact of traffic on air pollution in urban environments.

The goal of this research project was to fill this gap by monitoring air pollutants and traffic volume at high spatial resolutions to determine the impact of the COVID-19 lockdown on traffic and air pollution. To that end, we hypothesized that over the study period from lockdown to post lockdown, the lifting of stay-at-home orders would increase vehicle-related pollutants due to increases in traffic volume. The specific objectives to test this hypothesis were to (1) measure air quality pollutants on Milwaukee roads using a mobile-based sensor, (2) evaluate changes in traffic on Milwaukee roads using street-level traffic counts derived from smartphone data, and (3) explore the relationship between air quality changes and traffic data. Specifically, this project used a Sniffer4D air quality sensor that collected PM_1, $PM_{2.5}$, PM_{10}, NH_3, and $O_3 + NO_2$. These air pollutants were chosen because they (1) are driven by combustion emissions, including traffic, (2) have a direct impact on public health, and (3) were available through the mobile sensor technology that was provided. Ultimately, this work contributes to our understanding of how COVID lockdowns and traffic changes influenced air quality and more broadly the relationship between human activities and air pollutants in urban areas.

Methodology

Study area

A route for data collection within Milwaukee County was determined based upon criteria that included a spatial distribution across the city, a range in road types (highway and arterial), and the ability to complete the route within a 2-h drive. The final route chosen encompassed different areas of the city including downtown, several suburbs, and the lake shore, as well as a variety of road types (Fig. 1). In total, the

Fig. 1 Map of the route driven and a picture of the Sniffer 4D sensor on the roof to the vehicle
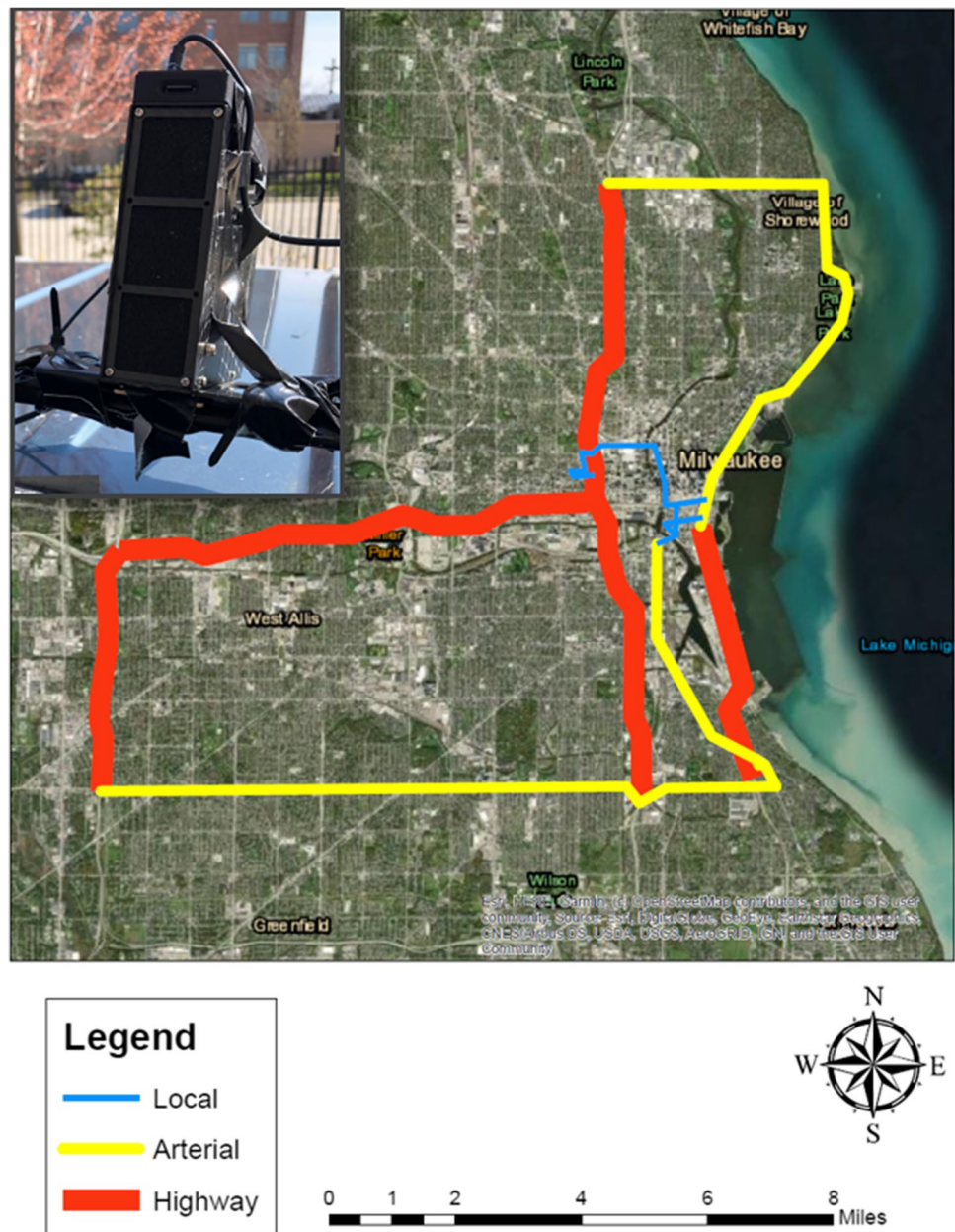
route covered over 74 km and took between one and a half to 2 h to complete depending upon traffic (Fig. 1).

Air pollutant data collection

Air quality was measured with a Sniffer 4D that was mounted to the roof of a vehicle (inset of Fig. 1). This sensor measured six air pollutants (PM_1, $PM_{2.5}$, PM_{10}, NH_3, H_2S, and $O_3 + NO_2$, without any speciation between O_3 and NO_2), as well as temperature, pressure, and humidity, and all data was referenced using an internal GPS unit. According to the manufacturer, the speed ranges of a typical car on roads or highways do not affect the accuracy of the data (Soarability 2023). After each route was completed, data

from the Sniffer 4D was downloaded from the sensor and processed using Sniffer 4D Mapper software. This software was used to visualize the magnitude and spatial distribution of the air quality data, as well as to format and export the data into text files. Next, these text files were imported into ESRI's ArcMap and transformed into point shapefiles using the latitude and longitude associated with each data point. These data points contained the date, time, pollutants measured, and latitude and longitude and were then used in the data analysis as described in a later section.

In total, we conducted 15 road surveys between April and August during which air pollutants were measured. Stay-athome orders were issued on March 24 in the State of Wisconsin and were lifted in Milwaukee County on June 11.

Therefore, the study does not capture conditions prior to the lockdown but does effectively cover a majority of the stay-at-home period and the months after the lifting of restrictions. Using the established route and Sniffer 4D sensor, we then selected days and times to collect data. Air pollution due to vehicles in metro areas occurs largely as a function of when commuters enter into and leave the city for work (Amin et al. 2017; Batterman et al. 2015); however, there may be different traffic patterns on the weekends depending upon subsistence, maintenance, and leisure (Agarwal 2004). Therefore, to capture both weekday and weekend trends, as well as peak traffic conditions, we collected data on Wednesdays and Saturdays between approximately 4 PM and 6 PM. Choosing a fixed time during the day also allowed us to maintain consistency in the data collection throughout the study period.

Traffic data collection

To evaluate trends in traffic volume over the sampling period, we obtained traffic data for individual road segments using smartphone-based vehicle volume data (StreetLight 2021). Using this data source, we determined both the total number of trips per day on each road segment, as well as the average number of trips during the sampling time period (4–6 PM). The estimated trip counts included all sampled bi-directional traffic sources including vehicles, trucks, and motorcycles. Data was collected on Wednesdays and Sundays around 4–6 PM between February 1 and August 31, 2020. This data was then applied to evaluate the change in traffic over time, as well as the relationship between traffic and air quality as discussed in the following section.

Data analysis

To evaluate the air quality and traffic along the route in this study, eight different road segments were chosen to analyze. These road segments chosen covered 75% of the total route and included four signalized arterial roads, which are Capitol (3.9 km), Lincoln (7.6 km), Oklahoma (12.5 km), and State Highway 32 (6.5 km), and four highways: I-43 (5.9 km), I-94 (8.9 km), I-41 (4.4 km), and I-794 (5.2 km). The air pollution data collected on each day was summarized for each individual road (i.e., mean, median, standard deviation). Using these summary statistics, the data across all days were analyzed for temporal trends to identify the effect of the lockdown order and subsequent re-opening on air quality within Milwaukee.

To do so, we performed two statistical analysis tests on the median air quality parameters for each road to determine if gradual or abrupt trends were present in the data. To evaluate if there were any gradual trends over time, we performed a Mann–Kendall test, which is a non-parametric test that

tests for the occurrence of a monotonic trend in the data (Helsel et al. 2020). To determine if there were any abrupt changes, we used the Pettitt test (Pettitt 1979). The Pettit test is an adaptation of the rank-based Mann–Whitney statistic that tests whether two samples come from the same population and is effective at detecting abrupt changes. For all tests, the significance level was set to 5%. By using both methods, we sought to detect whether the lifting of restrictions caused a gradual or abrupt increase in both air quality and traffic. In addition to tests of gradual and abrupt trends, we used the t-test to determine if the mean pollutant concentrations on each road were statistically different between samples during and after the lockdown.

To further evaluate the influence that traffic had on air quality, we performed simple linear regression to predict the average concentration of pollutants on each road based upon the number of total trips on the road from the smartphone-based traffic data. This is shown in the following equation:

$$y = \beta_0 + \beta_1 x_1$$

where y is the independent variable (i.e., average air quality concentration on a segment of a road), β represents the regression coefficients, and x represents the dependent variables (i.e., the volume of traffic on a segment of a road).

In addition, there were 3 days during the data collection period in which the previous 24 h had a rainfall depth that exceeded one inch (June 12, July 16, and August 11), which resulted in significant low outliers in the air pollutant data. This is most likely due to the effect that rainfall has on washing out pollutants (Luan et al. 2019; Ouyang et al. 2015a, b); therefore, to account for these meteorological effects on the data, these days were removed from the temporal analysis due to their influence and leverage on the dataset.

Results and discussion

Temporal trends in air quality

Detection of gradual and abrupt changes

Four of the measured pollutants (PM$_1$, PM$_{2.5}$, PM$_{10}$, and NH$_3$) displayed a statistically significant ($p < 0.05$) positive monotonic trend during the data collection period (April–August 2020) on all the roads as indicated by positive Kendall's Tau values in Fig. 2. These positive Kendall's Tau values indicated that over the course of the measurement period—from the beginning of the lockdown until the end of August—these pollutants were gradually increasing in concentration on the road segments (data shown in Fig. SI-1). While O$_3$ + NO$_2$ had positive Kendall's Tau values on each road segment, 7 of the 8 road segments were not statistically
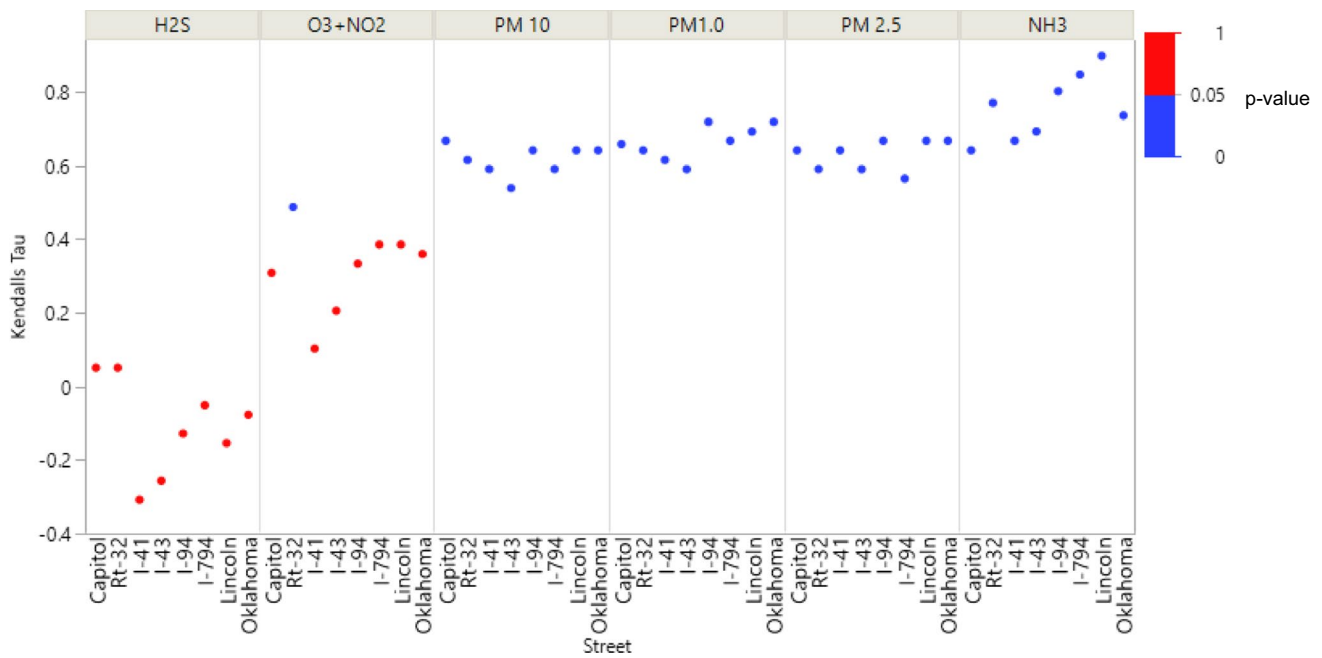
Fig. 2 Kendall's Tau and significance test for monotonic trends in air quality data. This figure illustrates Kendall's Tau value for each test, which represents the strength of a trend (-1 to 1) with those that are statistically significant ($p < 0.05$) shown in blue

Table 1 Results of the Pettit test on time series of mean pollutant concentrations

Road	$PM_{1.0}$	$PM_{2.5}$	PM_{10}	NH_3	$O_3 + NO_2$
Oklahoma	6/13	6/13	6/13	6/13	6/13
Lincoln	6/13	6/13	6/13	6/13	6/13
Capitol	6/13	6/13	6/13	6/17	6/13
Rt-32	6/13	6/13	6/13	6/13	6/13
I-794	6/13	6/13	6/13	5/16	6/13
I-94	6/13	6/13	6/13	6/17	6/13*
I-43	6/13	6/13	6/13	6/17	6/13*
I-41	6/13	6/13	6/17	6/17	7/4*

*Not statistically significant ($p < 0.05$)

significant. The exception to positive Kendall's Tau values was in H_2S, which while negative for six of the eight roads, none were statistically significant. These negative Kendall's Tau values and lack of statistical significance may be due to the fact that H_2S is not emitted in traffic or combustion emissions, and therefore less traffic and human activity may not result in changes in H_2S concentrations.

Using the Pettit test, a statistically significant ($p < 0.05$) abrupt change in pollution was detected for all roads for NH_3, PM_1, $PM_{2.5}$, and PM_{10} on or around June 13, 2020 (Table 1). In addition, for $O_3 + NO_2$, six of the roads (Oklahoma, Lincoln, Capitol, 794, 94, and 32) exhibited an abrupt increase in pollution on June 13, 2020. This date corresponds to 2 days after the lifting of Milwaukee County

lockdown measures on June 11, 2020. H_2S did not have any statistically significant abrupt changes and therefore was omitted from Table 1.

Differences during and after lockdown

The median air pollutant concentrations of all vehicle-emitted pollutants (PM_1, $PM_{2.5}$, PM_{10}, NH_3, and $O_3 + NO_2$) significantly increased after the lockdown was lifted ($p < 0.05$) based upon *t*-test. This finding is represented by Fig. 3, which illustrates the distribution of the mean air pollutant concentrations before and after the lockdown (June 11, 2020) across all eight roads. The mean PM_1, $PM_{2.5}$, and PM_{10} increased 307%, 270%, and 220%, respectively; the mean NH_3 and $O_3 + NO_2$ increased 277% and 28%, respectively. Finally, H_2S decreased 11%, but this was not statistically significant at the 0.05 level.

Trends in traffic

Traffic volumes derived from the smartphone-based traffic data indicates a clear change in traffic over the course of the lockdown. Figure 4 illustrates the mean Wednesday daily traffic volume for the eight segments of road evaluated in this study from February to August 2020. As illustrated, traffic began to suddenly decrease in the beginning of March after stay-at-home orders were issued for Milwaukee. Then, beginning in late March and early April, daily traffic volumes begin to increase before plateauing during the summer.
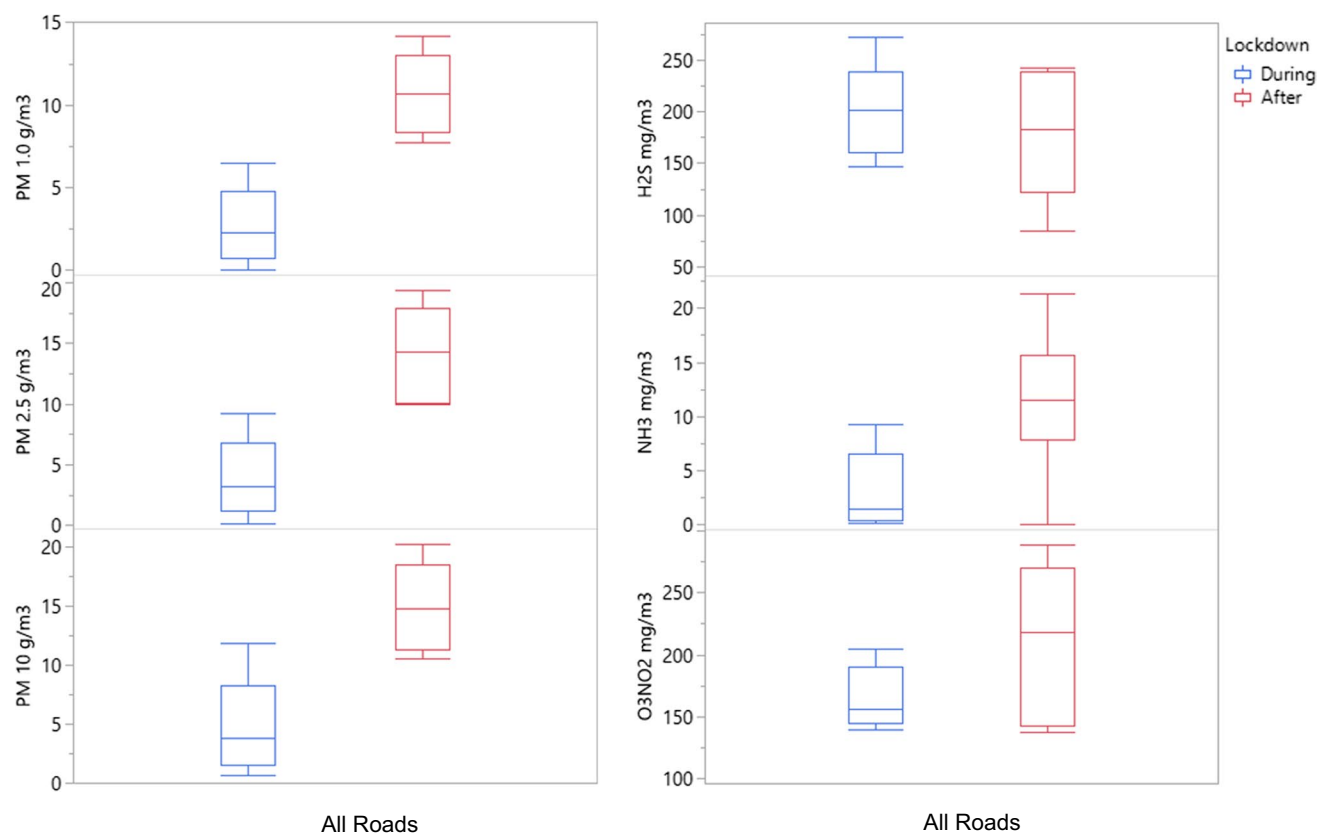
Fig. 3 Differences in the distribution of mean concentrations across all roads during and after the lockdown

To further evaluate these trends, we summarized the distribution of traffic volumes on each Wednesday during the lockdown (March 18–June 10) and after the lockdown (June 11–August 30) as illustrated in Fig. 5. All roads exhibited a statistically significant increase in traffic volume between 30 and 84%, with a median increase of 42% across all roads.

The Mann–Kendall and Pettit tests were used to detect if monotonic trends and abrupt shifts existed in the data from lockdown (March 18) until the end of August. As illustrated in Fig. 6, the traffic volume over the entire day showed statistically significant increasing monotonic trends, while the 4–6 pm traffic showed statistically significant increasing trends for 6 of 8 streets. The two roads that did not have statistically significant trends were arterial roads in the south of the city. A statistically significant abrupt shift was detected in the data from the Pettit test for all eight roads, and for six of the eight, this shift occurred on June 10 (Table 2). This date corresponds with the lifting of the Milwaukee County stay-at-home order on June 11, 2020. This date also corresponds closely with the time of the abrupt shifts that occurred in the air pollutant data (June 13). Because of the similarities between air pollutants and traffic volume as it relates to the change in mean values, increasing monotonic trends, and the timing of abrupt changes, the relationship

between air pollutant concentrations and traffic volume was evaluated as described in the following section.

Relationship between traffic and air pollutants

Linear regression was applied to predict the mean pollutant concentration on each road segment based upon the traffic volume over the measurement period (4–6 pm), and results indicated that the relationship varied broadly depending upon the road segment and the pollutant (Fig. 7). In terms of pollutants, particulate matter showed the strongest correlation with traffic explaining up to 56% of the variance (I-43) as indicated by the R^2 value, and a median of 33% across all particulate matter (PM_1, $PM_{2.5}$, and PM_{10}). In general, all three particulate matter sensors had similar relationships with a stronger correlation for smaller particles with few exceptions. Traffic explained up to 43% of the variance in $O_3 + NO_2$ concentrations with a median of 29%. Finally, traffic explained up to 47% of the variance in NH_3 concentrations with a median of 22%.

Results from the linear regression suggest that the relationship between pollutants and traffic vary by road. Lincoln Avenue had the highest correlations with traffic explaining 43–52% of the variance in vehicle-based pollutants. This
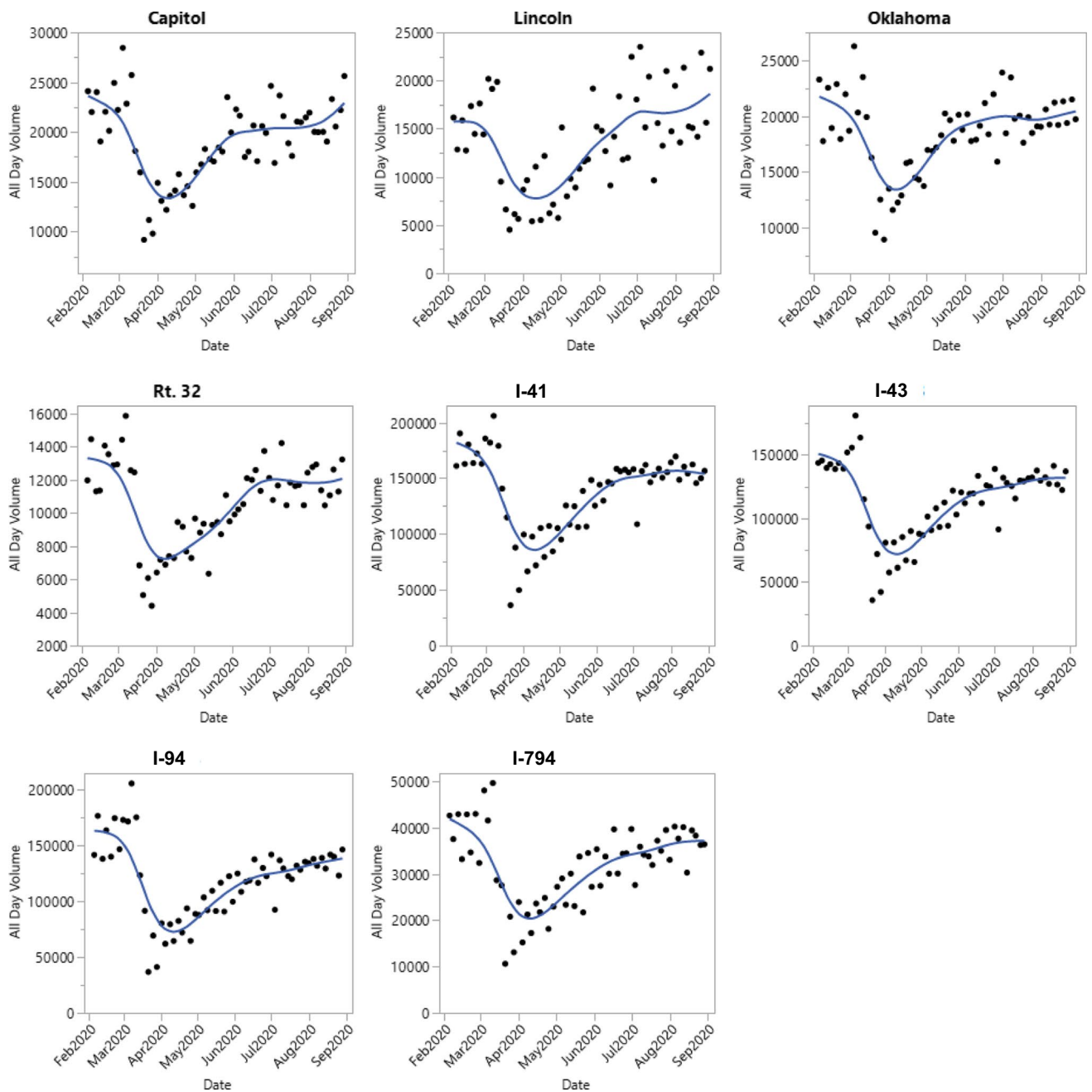
Fig. 4 Graph of the weekday 24-h traffic count from February through the end of August 2020 with a moving average trendline

segment of road runs north and south along the shoreline of Lake Michigan and for several miles is buffeted by a cliff face. Therefore, this segment of the road may be less impacted by other anthropogenic sources of pollutants. In general, the goodness of fit is lowest for roads in the southwest portion of the study area (e.g., Fig. 8), with no statistically significant trends for Rt-32 and Oklahoma. These are signalized arterial roads that are subject to stopping, idling, and starting, which may impact emissions, unlike the uninterrupted flow on the interstate highways. Additionally, both

Rt-32 and Oklahoma were found to have no statistically significant monotonic increasing trend in the 4–6 PM traffic volume over this time period. Therefore, given the lack of a trend in the traffic data, it is not surprising to see little correlation between traffic volume on these roads and changes in air pollutants. In addition, these roads are near land uses that are dominated by commercial and heavy industrial, which may explain the lack of correlation between the measured pollutants and traffic volume due to other surrounding anthropogenic sources of air pollutants.
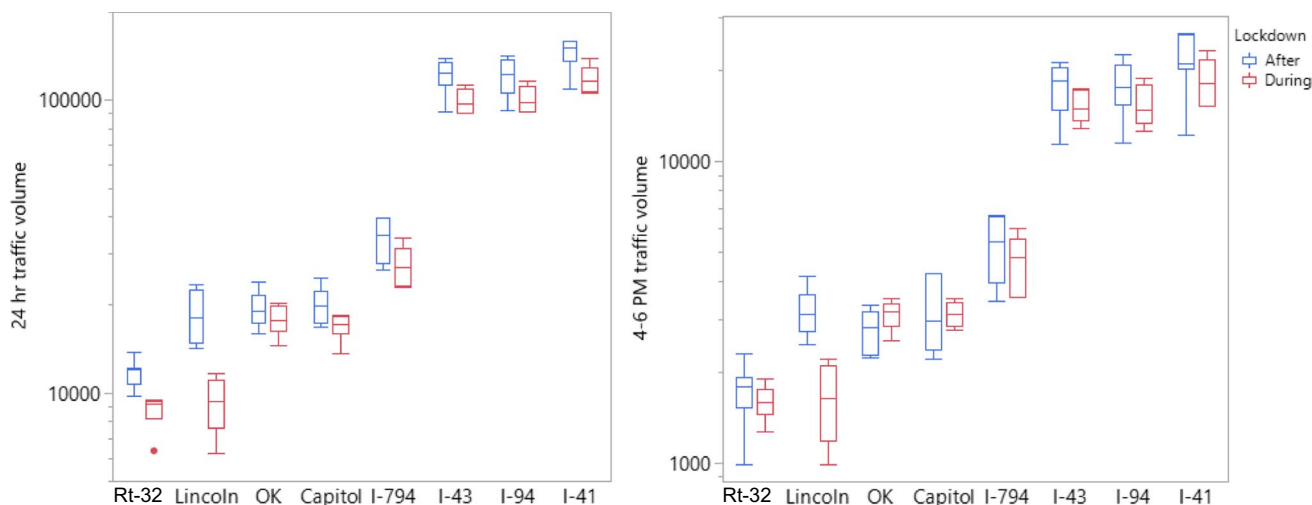
Fig. 5 Distribution of weekday traffic on each road during (March 18–June 10) and after (June 17–August 26) for the 24-h traffic volume (**left**) and 4–6 PM traffic volume (**right**)

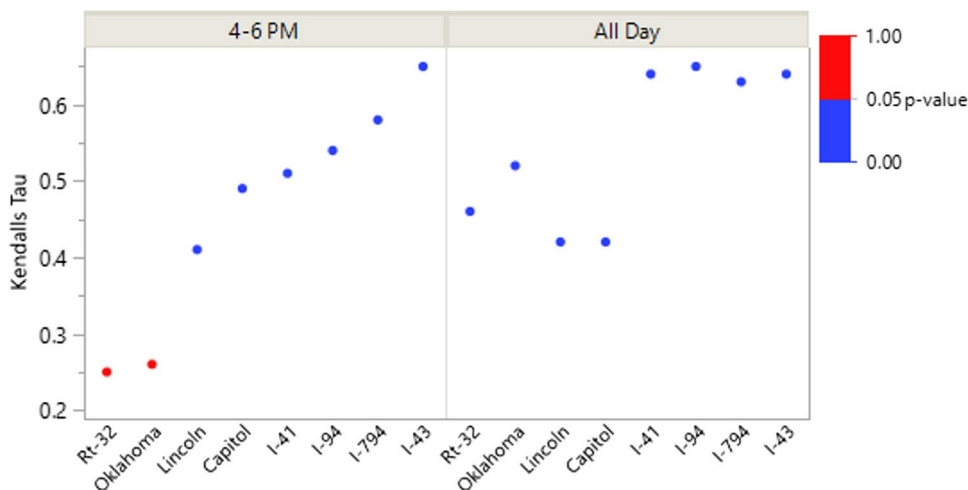**Fig. 6** Mann–Kendall test of the traffic volume for 24 h and 4–6 PM on weekdays

Table 2 Results of abrupt changes in traffic on weekdays from the Pettit test

Road	Date	p Value
Capitol	20-May-20	0.025
Lincoln Ave	20-May-20	0.029
Oklahoma	10-Jun-20	0.005
Rt. 32	10-Jun-20	0.002
I-41	10-Jun-20	0.001
I-43	10-Jun-20	< 0.0001
I-794	10-Jun-20	0.001
I-94	10-Jun-20	< 0.0001

Discussion

This study captured the changes in air pollution and traffic volume in Milwaukee, WI, a city of approximately one million people, during the COVID-19 lockdown. Results demonstrated that air pollutants were found to increase from lockdown to post lockdown, including increases in mean concentrations of NH_3 (277%), particulate matter (220–307%), and $O_3 + NO_2$ (28%). The increase in $O_3 + NO_2$ once the lockdown was lifted may be largely due to increased traffic emissions of NO_2. Other studies found that during COVID-19 lockdowns, the NO2 levels decreased, while O_3 levels either remained unchanged or increased (Gkatzelis et al. 2021; Gualtieri et al. 2020), with the increase in O_3 attributed largely to the reduction of nitrogen oxide that leads to a lower O3 consumption or titration. This was followed by a subsequent increase in NO_2 and decrease in O_3 once the lockdown was lifted (Ropkins and Tate 2021). Tests for abrupt changes demonstrated that for all combustion pollutants, there was a change that occurred on June 13, 2020 on most roads.
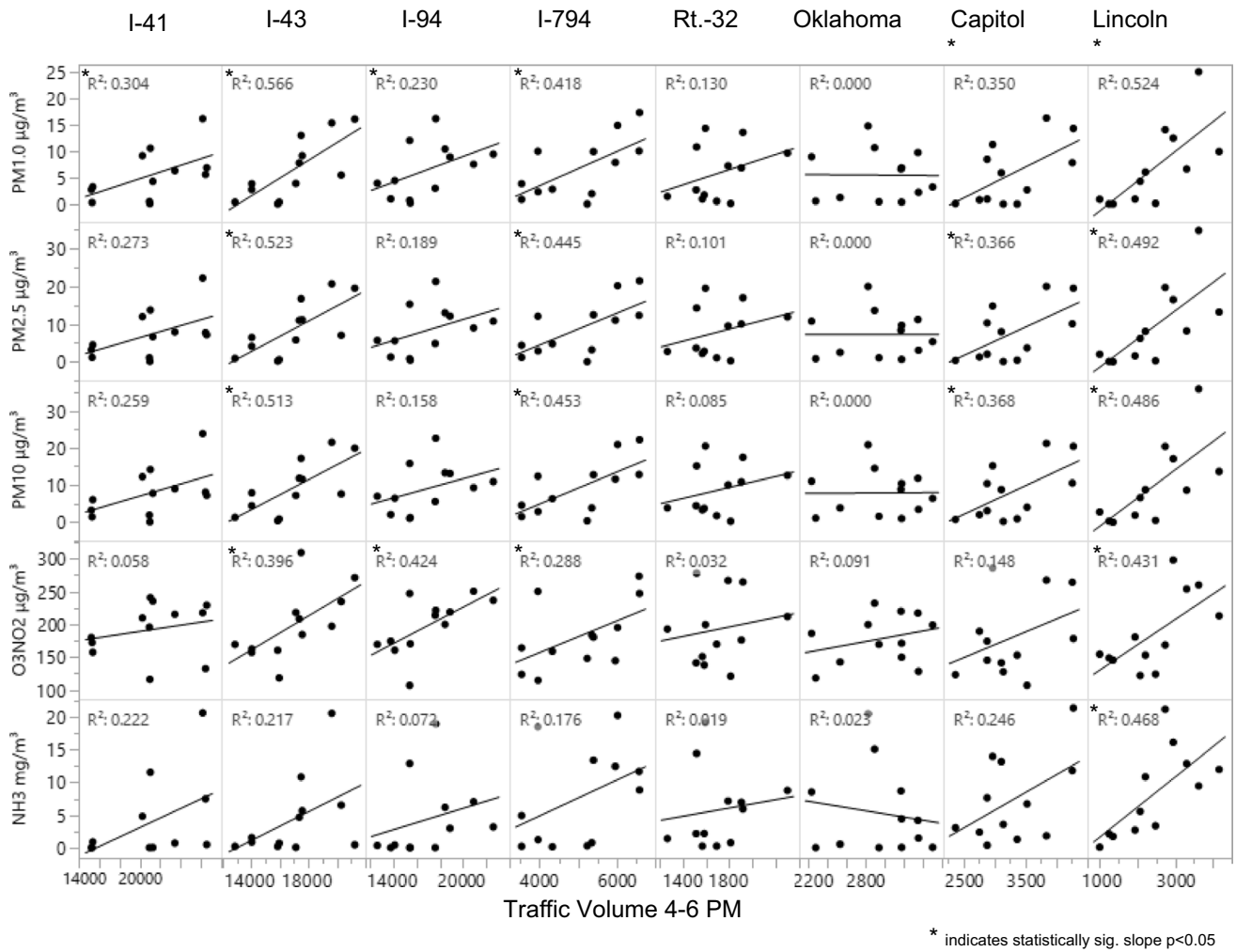
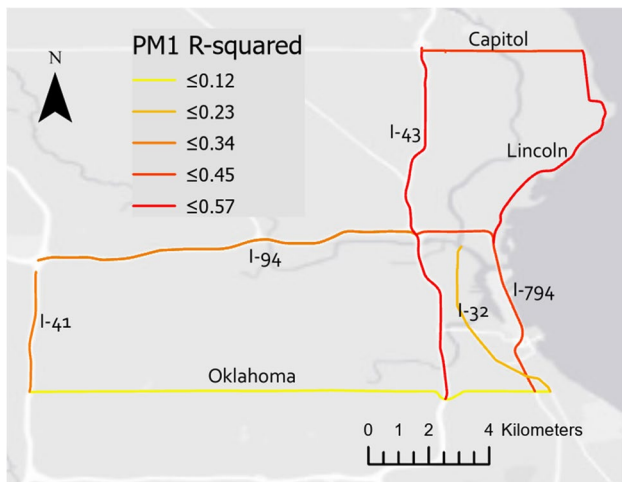**Fig. 7** Relationships between pollutants and traffic volume for each road segment

Fig. 8 Spatial distribution of the goodness of fit (R^2) for $PM_{1.0}$

This corresponds to shortly after the lockdown was lifted, indicating that the lockdowns had a direct impact on air quality.

In addition to changes in air pollution, traffic increased from lockdown to post-lockdown by 30–84%, depending upon the road. These findings correspond to other studies that found similar changes in traffic in other studies within the USA (Hudda et al. 2020; Jia et al. 2020; Xiang et al. 2020). Mann Kendall tests confirmed a monotonically increasing trend in traffic from the time the lockdown occurred until the end of the monitoring period, and a Pettit test for abrupt changes confirmed a change in traffic patterns near the lifting of the lockdowns on June 11, 2020. Therefore, due to the observed similarities in air pollutants and traffic volume, we sought to evaluate the influence that traffic has on explaining the variance in air pollutant concentrations.

The results from the linear regression reveal that traffic was able to explain some of the variances in the pollutant

concentrations, including up to 47% of NH_3 (median 22%), 57% of particulate matter (median 33%), and 42% of $O_3 + NO_2$ (median 29%). These estimates are within the broad range of other studies that have estimated the impact that traffic had on the reduction in air pollutants during the lockdown (Hudda et al. 2020; Jia et al. 2020; Wang et al. 2020a, b; Wang et al. 2020a, b; Xiang et al. 2020). However, these previous studies were either temporally constrained to traffic data at an average daily or hourly interval, spatially constrained to traffic and air pollutant data at single point sources, or both. Those that do use mobile-based sensors (Hudda et al. 2020; Wang et al. 2020a, b) were able to evaluate changes in air quality and differences between road types; however, these studies were also constrained to traffic data at single points on a highway within the road network, requiring assumptions in traffic changes on roads for which traffic data was not available.

An advantage of this study is the use of both mobile-based pollutant sensors and localized traffic volume data to evaluate changes at road-level spatial scales. Specifically, we were able to leverage this data to evaluate the differences in pollutant concentrations across road types and regions of the city, as well as compare changes in air pollutants to local traffic conditions at the source where data was collected. In doing so, we found that while both air pollutants and traffic increased on all roads over the study period and have abrupt changes at similar times, the correlation of traffic volume to air pollutant concentrations varied widely. This could be due to the unique conditions at the site-level that control air pollutant concentrations near the roads. For example, Lincoln Drive has the strongest relationship between pollutants and traffic, which could be due to the location between the lake and a cliff face making local air quality more dependent upon road traffic than other locations that are nearer to industrial and commercial centers of the region.

Furthermore, arterial roads in the south of the city were found to have little to no relationship between traffic and combustion-related air pollutants. This may be because these roads exhibited no statistically significant changes in traffic during the 4–6 PM data collection period. If these street-specific traffic volume data were not available for this study, a generalization of traffic changes across the city may have resulted in a type I error that incorrectly attributed changes in air pollutants to changes in local traffic. In addition, these locations are closer to industrial and commercial areas of the city where other sources of combustion pollutants may be present or dominate air pollutant concentrations. This aligns with other studies using mobile-based sensors that have similarly found streets near industrial and commercial areas where industrial emissions make up the most significant portion of pollutants (Wang et al. 2020a, b). Overall, these outcomes highlight the value of air quality data at

relevant spatial and temporal scales for assessing the influence of traffic on air pollutants in urban areas.

There are several limitations that influence the interpretation of this study. First, this study does not have data on air pollutants prior to the lockdown nor does it have data on air pollutants in previous years during the same seasons. Therefore, there is no way to account for seasonal effects or yearly trends that may be occurring within the air pollutant data itself. However, the strong changes, coupled with supporting literature, largely support the attributions of traffic to changes in air pollutants articulated in this study. Secondly, this study does not capture the variation in other sources of pollutants or background concentrations and is limited to evaluating changes in traffic only. There may be other sources, such as industrial activity, airports, or power plants, that may make up a significant portion of the source from local areas. A simple dispersion modeling (briefly discussed in the Appendix) using AERMOD (U.S. EPA 2022) performed on two of the road segments showed that the background concentration have non-negligible effect in the local variation of pollutants. Finally, as this data is limited to Milwaukee, WI, the findings from this study may not translate to other cities that have different meteorological and anthropogenic characteristics that influence air pollutants.

What impact these changes at a local scale have on air pollutant concentrations more regionally is also unclear. A synthesis of $PM_{2.5}$ and ozone concentrations during the lockdowns across the USA found a variation in changes in those pollutants, with some increasing and others decreasing (Bekbulat et al. 2020). This may be due to meteorological or regional influences on $PM_{2.5}$ and ozone that contribute to regional concentrations. In fact, recently, it has been found that more than half of premature mortality from air pollution can come from out-of-state pollutant sources (Dedoussi et al. 2020). Therefore, it may be challenging to make regional inferences on pollutant concentrations from this localized data.

Overall, these results have important implications for the management of air pollutants. The reduction in traffic due to the COVID-19 lockdowns provided an opportunity to evaluate and test the impact of traffic reductions on the environment, which in turn can help inform management decisions. For example, the World Health Organization recommends a 5 $\mu g/m^3$ annual mean concentration for $PM_{2.5}$ due to the adverse impact that it has on public health (World Health Organization 2021). In this study, $PM_{2.5}$ had a median concentration of 3 $\mu g/m^3$ across all roads during the lockdown, while the lifting of the lockdown increased median concentrations to 13 $\mu g/m^3$—exceeding recommended concentrations. Therefore, this study shows that this type of intervention could be effective at reducing concentrations of $PM_{2.5}$ to levels that are closer to WHO recommendations. To that end, long-term solutions may be achieved by changes in

both vehicle composition (e.g., transition from combustion engines to electric vehicles) or the mode of traffic (e.g., shift from passenger cars to public transportation). As such, these results, among other findings, can be utilized by decision-makers to inform management decisions related to traffic and air pollution.

Conclusions

This study presents an analysis of the air pollutant and traffic changes during the COVID lockdown in Milwaukee, WI. Results indicated that the lifting of the lockdown measures resulted in statistically significant monotonic increases in both traffic volume and air pollutant concentrations over the study period, and abrupt changes in traffic volume and air pollutant concentrations near the time Milwaukee County lockdown restrictions were lifted. Traffic volume was able to explain up to 42–57% of the variance in air pollutants on roads. These findings, therefore, have practical implications at the intersection of traffic management and air quality in urban areas.

Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to their large size but are available from the corresponding author on reasonable request.

Declarations

Ethical approval This study did not involve human or animal subjects and therefore did not require ethical approval.

Consent to participate This study did not involve human or animal subjects and therefore did not require consent to participate.

Consent for publication This study did not contain any induvial person's data.

Competing interests The authors declare no competing interests.

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